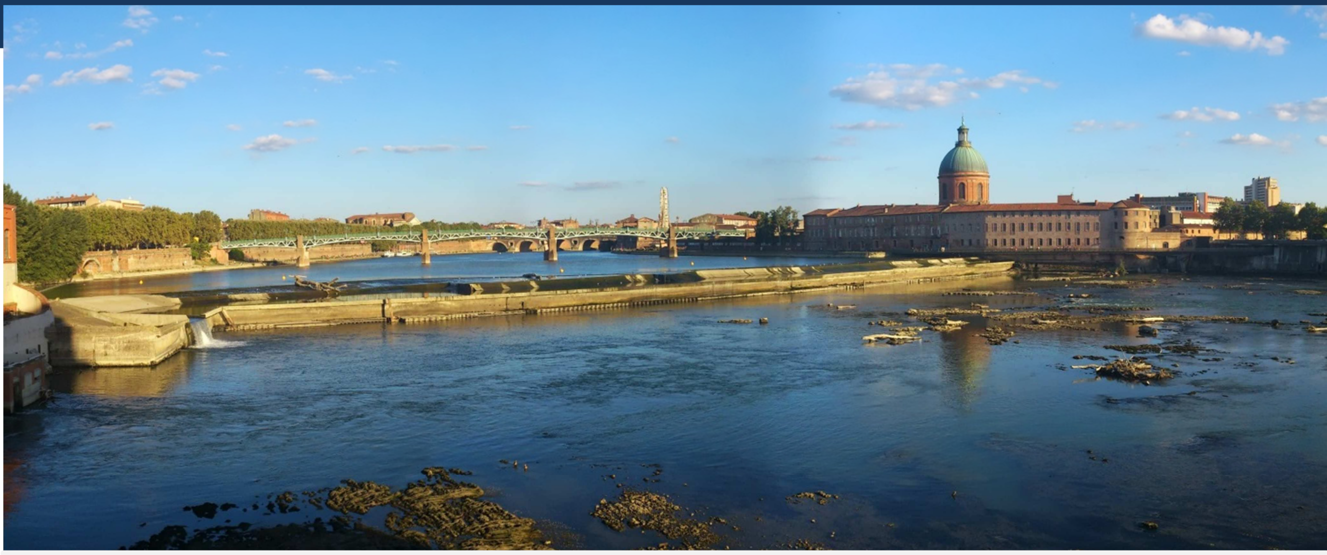

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Mental Workload Classification with fNIRS using Temporal Convolutional Networks

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Content

Neuroimaging classification with functional Near Infrared Spectroscopy (fNIRS) can be used for applications such as Brain Computer Interface (BCI) and Brain Machine Interface (BMI). BCI/BMI provide a means for decoding brain signals into actions, thus providing a means of communication for people suffering with paralysis such as conditions such as locked-in syndrome (LIS), spinal cord injury [3].
This paper demonstrates that fNIRS can be used effectively for BCI using four-way classification of left and right motor imagery (MI), mental arithmetic (MA) and rest tasks. 36-channel fNIRS data, capturing hemodynamic signals from frontal, motor and visual cortex from 29 subjects during an experimental paradigm consisting of left, right motor imagery, mental arithmetic and rest states is used. The data is obtained from an open access dataset 1. Each experiment in 1 consisted of six sessions: three sessions of left and right-hand MI and three sessions of MA and baseline tasks (taking a rest without any thought). Each session consisted of a 60-s pre- and post-experiment rest period, and 20 repetitions of the task (LMI/RMI/MA/rest). fNIRS optical intensity signals are converted into HbO and HbR concentration changes using modified Beer Lambert Law (mBLL). The fNIRS sampling frequency is 10-Hz. HbO and HbR are applied to a third-order bandpass Chebyshev filter with cut-off frequencies of 0.01-Hz and 0.1-Hz to attenuate physiological noise caused by respiration, motion artifact and heartbeat.
Traditional classification techniques, such as SVM and KNN, require feature-selection including mean, standard deviation and kurtosis and preprocessing, which do not necessarily result in optimum classification. To avoid the requirement for manual feature selection, the use of Temporal Convolutional Networks (TCN) [2] is proposed for the classification of fNIRS time-series with minimum pre-processing, and without requiring feature extraction. TCN utilizes stacked residual blocks, where the core element of a residual block is a dilated causal convolutional neural network with scaled dilation factors d, with multiple values such as 1, 2, 4, 8, 16, 32, 64. A dilated convolution is a type of convolution where the filter length is programmed by dilations across layers [4]. Dilated convolution is used to achieve a larger receptive field with a small number of parameters and layers, and thus can be significantly more efficient than a recurrent neural network. Two dilated causal convolution networks with rectified linear unit (ReLU) activation are stacked to form the residual block. A kernel size of 8 is chosen for the network. The receptive field for the causal convolution layer is calculated using F(n) = F(n-1) + [kernel size(n)-1] * dilation(n). The deep neural network is trained and tested on all subjects. The average classification accuracy using fNIRS across all subjects for LMI vs. RMI is 76.8% (59% in 1) and MA vs. rest is 85.1% (81% in 1) and the four-class classification is 66.5%. The average classification accuracy for MA vs rest is better than LMI vs RMI as the subjects are prone to fatigue and sleepiness during motor imagery tasks 1. LMI vs RMI accuracy and the four-class classification accuracy can potentially be improved by improving the motor imagery data collection.

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